# EXTRACTING PERSONAL CHARACTERISTICS FROM HUMAN MOVEMENT

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## ABSTRACT

In this paper, we propose a new method for extracting personal characteristics from 3D body movement. We introduce the eigen action space to represent the personal characteristics. First, we estimate the average action from a set of 3D pose parameters from different people. Then we created the eigen action space from the covariance matrices of 3D pose parameters using KL transform. Because the eigen action space consists of orthogonal base vectors, 3D pose parameters of a person is represented as a point. Similarity measure is calculated from points in action eigen space. Also, actions with new personal characteristics can be reconstructed by sampling new points in the eigen action space.

## 1. INTRODUCTION

Estimation of the personal characteristics from the body movement is important for many applications such as building virtual actors and personal identification system. For example, if we can represent the personal characteristics of body movement in a few parameters, we would be able to synthesize human actions with various characteristics.

Many researches focused on the recognition of various actions within a few people using DTW, HMM [2,3] and phase space[6]. The personal characteristics have been considered as *noise* component within action recognition frameworks. Murase et. al. identified persons from walking pattern using the parametric eigenspace method [5]. However, they use the apparent 2D images, and directly project intensity pattern into the eigenspace. Personal characteristics of the 3D body pose are not investigated.

In this paper, we propose a new technique for extracting personal characteristics of 3D body movement. We introduce the *eigen action space* to represent the personal characteristics. First, we created the average action from the 3D pose parameters from different people. Then we created the eigen action space from the covariance matrices of 3D pose parameters using KL transform. Because the eigen action space consists of orthogonal base vectors, 3D pose parameters of a person are transformed into a point. Actions with new personal characteristics can be reconstructed by sampling points in the eigen action space.

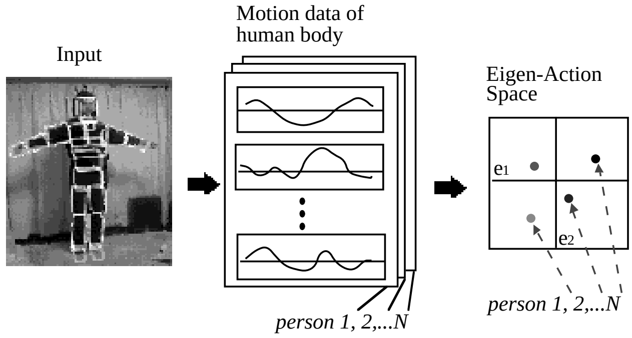



Figure 1: Overview of the eigen action method

## 2. OVERVIEW

Fig. 1 shows the overview of the proposed eigen action method. First, we estimate 3D pose data of human from video. We use 3D human model in Fig.2 to estimate the pose parameters of each parts. We represent a human body by an articulated structure consisting of 10 rigid parts corresponding body, head, upper arms, under arms, upper legs, under legs. The motion parameters are estimated using the spatial-temporal gradient method, and automatic initial registration with silhouette [1].

Then, we estimate the personal characteristics of the 3D pose parameters. We introduce three different pose parameters to describe characteristics of the body movement.

**average action**: average of pose parameters of the same action from different people.

**difference action**: difference of pose parameters between the average action and each persons action.

**eigen action**: pose parameters estimated from the covariance of 3D pose of different persons using KL transform.

## 3. EIGEN ACTION SPACE

### 3.1 Average action and different action

Let the 3D pose parameters $x_p$ of person $p$ be a vector

$$x_p = [\psi_0^p, \psi_1^p, \psi_2^p, .... \psi_l^p]^T \qquad (1)$$

where $l$ is the number of frames. The size of the pose parameters $x_p$ is $k*l$ where $k$ is the number of the pose parameters. The average action $c$ can be estimated as

$$c = \frac{1}{N}\sum_{p=1}^{N} x_p \tag{2}$$

where $N$ is the number of the person used for training. The difference action $D_p$ can be written as

$$D_p = x_p - c \tag{3}$$

### 3.2 Eigen action

The covariance matrices of the pose parameters $Q$ is

$$Q = XX^T \tag{4}$$

where $X = [D_1, D_2, ...D_p]$. Eigen vector and eigen value can be obtained from the following equation.

$$Qu_k = \lambda_k u_k \tag{5}$$

The problem of estimating eigenvector and eigenvalue from Eq.(5) is that $m*n$ solutions exist. Therefore we need to reduce the computational costs. Let us consider the following eigen equation

$$X^T X\, v_i = \mu_i v_i \tag{5}$$

Eq.6 has only $N$ eigen vector. To clarify the relationship of Eq.6 with Eq.5, we multiply $X$ to the both sides of Eq.5.

$$X\, X^T X\, v_i = \mu_i X\, v_i \tag{6}$$

If we compare Eq.7 and Eq.5, we see

$$X\, X^T (X\, v_i) = \mu_i (X\, v_i) \tag{7}$$

Therefore $X\, v_i$ is the eigen vector of $Q = XX^T$. We can estimate $u_i$ by calculating $v_i$ and

$$u_k = X\, v_i \tag{8}$$

In this paper, we call the eigen vectors $u_i$ as *eigen action vectors* and used for the feature space to extract personal characteristics of human movement.

## 4. ESTIMATING PERSONAL CHARACTERISTICS

### 4.1 Projection onto eigen action space

Because the eigen action space consists of orthogonal base vectors, 3D pose parameters of each persons are represented as a point. The personal parameters $g_p$ can be estimated as

$$g_p = [u_1, u_2, ....u_k]^T (x_p - c) \tag{9}$$

The distance between the actions is

$$d = \left\| g_p - g_q \right\| \tag{10}$$

where $g_p$, $g_q$ are the personal parameters from the different people. When the new personal parameters $g_q$ is obtained, The most similar person can be estimated as

$$p = \arg\min_{1 \le p \le N} \left\| g_p - g_q \right\| \tag{11}$$

### 4.2 Reconstruction of the 3D pose parameters

3D pose parameters can be reconstructed from a point in the eigen action space. The 3D pose parameters $x_p$ of the personal parameter $g_p$ are

$$x_p = \sum_{i=1}^{N} g_p u_i + c \tag{12}$$

The personal parameter $g_p$ can be any points in the eigen action space. Therefore we can synthesize the new 3D action with the different personal characteristics from that of training actions.

## 5. EXPERIMENTS

### 5.1 Estimating Eigen Action Space

We select one typical action from the gymnastic exercises (stretching). A person lift up both hands in vertical direction [1~35 frames], pose a little at the top [around 35 frames], and lift down both hands in horizontal direction [35~70 frames]. Fig.2 shows the example input images. We have estimated 3D position of the each body parts. 30 parameters except the body translation are used for experiments. The beginning and end of the action is normalized at 70 frames.

Fig. 3 shows the average action of eight subjects. The small personal difference is eliminated, and the basic structure of the action is presented. We created the eigen action space from the covariance matrices of 3D pose parameters using KL transform. Fig.4 shows the eigen action vectors. We show eigen action vectors ($u_1$,$u_2$,$u_3$) with the three biggest eigen values.

Fig.4 (a) shows that the pose parameters of the upper legs (*lu_arm*, *ru_arm*) are prominent which corresponds to the velocity difference between the lift-up and lift-down action. There is little personal difference around the 35 frame because both hands of all the subjects are still above the head. The personal difference of the head, body, and waist is relatively smaller, but we can see the difference from 35 frame to 70 frames.

Fig.4 (b) shows the personal difference of the upper arm angles (*lu_arm*, *ru_arm*) around the 35 frame and the 60 frames. The different peak of the right and left upper arms show that 3D positions are not symmetrical. The angle difference of upper legs (*lu_leg*, *ru_leg*) and lower legs (*ll_leg*,

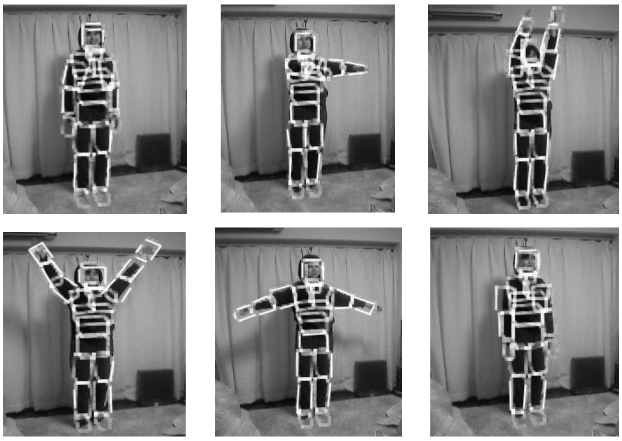


Figure 2: Tracking persons using video sequences

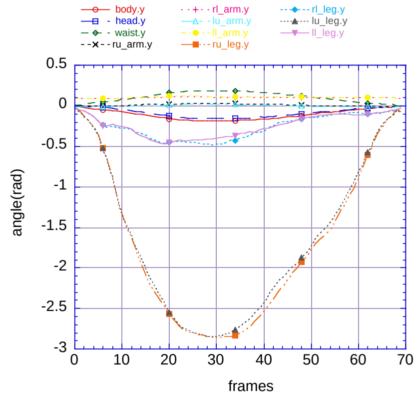
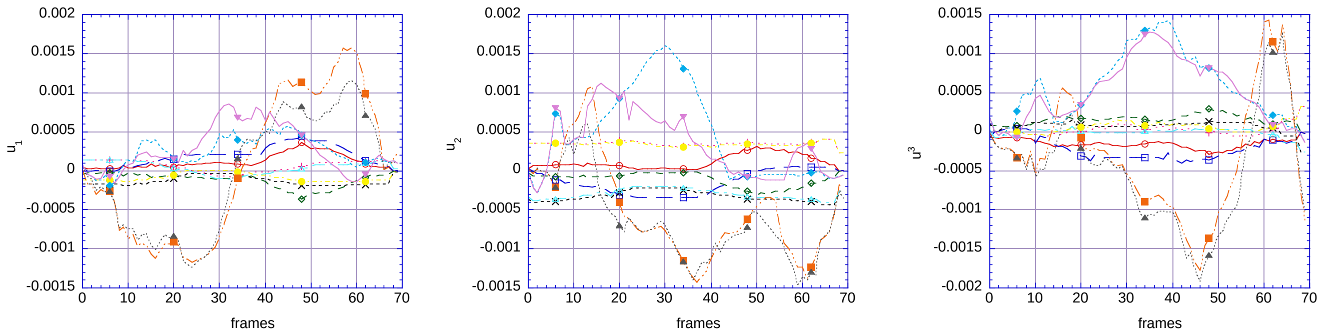



Figure 3: Pose parameters of the average action




(a) $u_1$ (b) $u_2$ (c) $u_3$

Figure 4: Time sequences of eigen actions

*rl_leg*) are static at +0.0004 and -0.0004.

Fig.4 (c) shows the personal difference of the lower arm angles (*ll_arm*, *rl_arm*) around 35 frames. The angle of the upper arms are asymmetrical around 55 frames which shows that the position are difference between subjects.

Fig. 5 shows the personal points in eigen action space. In Fig.7, we selected the two largest eigenvectors for the display purpose. Distance in the eigen action space represent the similarity of the actions. For example, the most similar action of the person E is the person B. In the contrast, the most different actions of the person E is the person D.Fig. 6 shows the sample points from the same person. We can see that the interpersonal difference is relatively smaller.

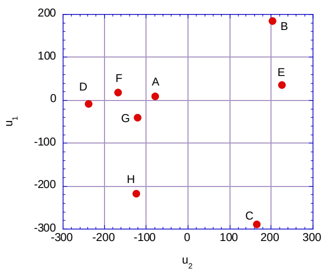



Figure 5: Actions of each subjects projected onto eigen action space

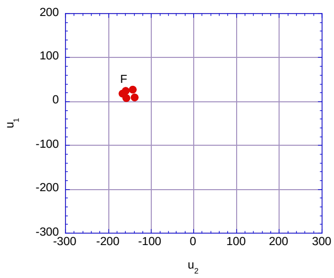
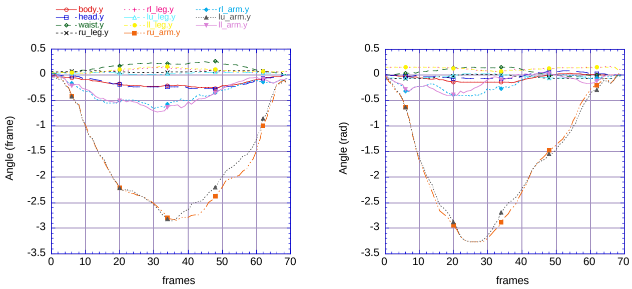



Figure 6: Actions of one subject projected onto eigen action space

### 5.2 Synthesizing new actions with different personal characteristics

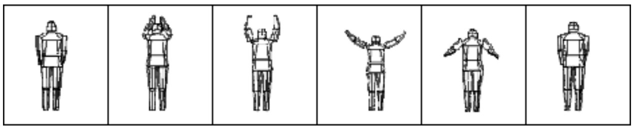
Fig. 7 shows the example of the synthesizing new action of the different personal characteristics. We use the three largest eigen action vectors ($u_1$, $u_2$, $u_3$) in Fig.4. Fig.7 shows examples (a) $p_1$=(400, 0 ,0), (b) $p_2$=(0, 400, 0 ). We compare the new action with the average action. Fig.8(a) shows the 3D pose of the average actions. (b) shows the synthesized action of Fig. 7(a). We can confirm that the 3D pose is also visually different.

Fig. 9 shows the example of action synthesis to the dance sequences. (a) is the average action of five subjects. (b) shows the two different example of action synthesis with different personal characters.

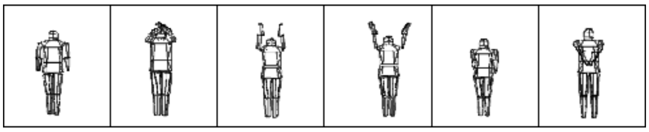



(a) $p_1$= (400,0,0) (b) $p_2$= (0,400,0)

Figure 7: Generating new actions of different personal characteristics



(a) 3D pose of the average action



(b) 3D pose of the action Fig.7(a)

Figure 8: Comparing the average action and the synthesized action

### 5.2 Synthesizing new actions with different motion patterns

The proposed method can be applied for synthesis-by-analysis of different action patterns. In this case, the inputs to the algorithm are segments of different actions. The average action and eigen action space are estimated as described in Sec.3. Various action segments can be synthesized using the linear combination of eigen action vector. Fig. 10 shows the example of generating dance sequences.

## 6. CONCLUSION

In this paper, we proposed a new method for extracting personal characteristics from 3D human movement. We introduced the eigen action space to represent personal characteristics of human movement. In this paper, we presented the experimental results using the real video sequences, and the personal difference has represented using the eigen action space.

## 7. REFERENCES

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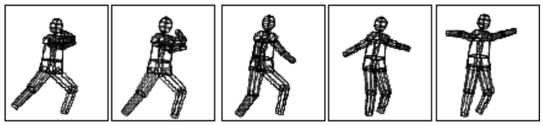
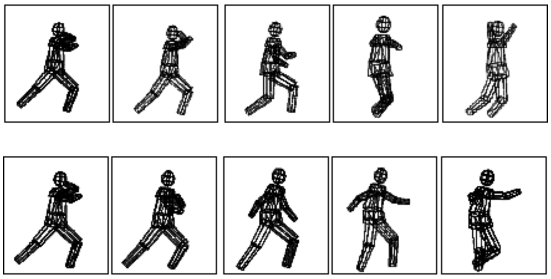
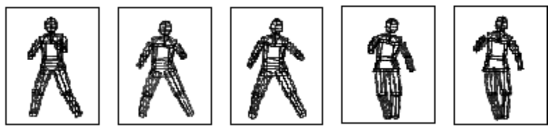


(a) 3D pose of the average action

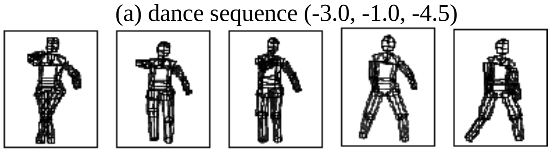


(b) Synthesizing new personal characteristics

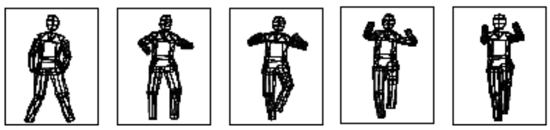
Figure 9: Example of generating a dance sequence with different personal characters



(a) dance sequence (-3.0, -1.0, -4.5)



(b) dance sequence (-4.0, -1.0, 0.0)



(c) dance sequence (1.0, 6.0, 0.5)

Figure 10: Example of generating various dance sequence